The Structure and Evolution of Online Rating Biases in the Sharing Economy

Research-in-Progress

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Abstract

A wave of sharing economy companies are profoundly changing the market landscape, disrupting traditional businesses alongside the social fabrics of exchange. A critical challenge to their growth, however, is that how to generate trust from online to offline transactions. Users in many online platforms rely on reputational systems such as ratings to infer quality and make decisions. However, ratings are biased by behavioral tendencies, such as homophily and power dependence. Our project examines the structure and evolution of rating biases by analyzing massive amount of platform data. Using big data techniques on leading sharing economy platforms, we identify the structure and evolution of biases, attempting to correct the tendencies in system design. We examine rating biases and their relationships to social distance among heterogeneous user populations. The coevolution of reputational systems and trust further implies long-term behavioral trends, which are critical to investigate for business growth.

Keywords: sharing economy, rating bias, social network, trust

Introduction

A wave of sharing economy platforms has produced a billion-dollar industry that is profoundly changing the way that people exchange with one another. Leading technology giants, such as Uber, Airbnb, and Zipcars, disrupt traditional markets, producing tensions in the social fabrics as an emerging trend of innovative business models (Greenwood and Wattal 2017; Zervas et al. 2017). Unlike traditional firms, the sharing economy uses technology-mediated markets in which users engage in peer-to-peer (P2P) exchanges where they are both consumers and providers (Hamari et al. 2016). A critical challenge to sharing economy platforms is the risk that comes with online information uncertainty, which is further carried offline and magnified in interpersonal transactions. Being chauffeured by a stranger to work, and sharing a room with an unfamiliar guest, involve significant personal risks compared to other ecommerce markets where transactions largely remain online. Trust is hence a critical aspect of P2P exchange (Paul and McDaniel 2004), and it is facilitated by online reputation systems that signal quality through ratings (Abrahao et al. 2017).

While ratings provide important feedback channels that assist future transactions, they are subject to varied biases from user-generated content (Filippas et al. 2018; Li and Hitt 2008). These biases present a fundamental challenge to the growth of online platforms in general, as they distort quality evaluation and affect trust in market exchange. Identifying the sources and structures of biases while providing practical solutions is the driving goal of this project. Three issues are particularly important to understanding rating biases: 1) How does social similarity or distance affect user evaluation of exchange relations, and how do rating patterns vary among heterogeneous populations? 2) What are the dynamic trends of behavioral biases, and how do they co-evolve with user experience? 3) How to reduce rating bias in system design based on an understanding of its structure and evolution? Addressing these issues provides an important step towards counteracting behavioral tendencies that limit the long-term growth of the sharing economy, as well as other online markets with significant interpersonal risks.

Theory of Social Bias and Online Rating Systems

The formation of exchange relations is typically subject to varied biases based on people's perceived characteristics. Social bias in mutual evaluation processes is first related to differences along demographic dimensions. The classical theory of homophily suggests that connections are more likely to form among similar individuals, producing local clustering patterns based on shared characteristics (Blau 1977; McPherson et al. 2001). Critical to the theory of homophily is the implication that differences among demographic characteristics translate into social distance, which biases the likelihood of tie formation as well as the evaluation of interactions.

Notably, the social distance bias is amplified in power-dependent exchange relations. As social exchanges frequently involve two parties with unequal power and resources, the party is more dependent if one relies on the other for achieving goals while having limited alternatives (Emerson 1962). Power and dependency are further related to one's network position, which reflects connectivity and the availability of alternatives. Those in centralized positions display more power and less reciprocity over time, producing biased treatment of the lower-status party (Cook et al. 1983; Lazarsfeld and Merton 1954). This further implies that socially distant exchange parties in lower positions are likely to receive less favorable evaluations, based on biases from both homophily and power dependence.

Whereas the homophily (or distance) bias is typically attributed to latent boundaries in social grouping, it also has an informational aspect: Perceived similarities among individuals who engage in market exchange reduces uncertainty when other evaluation signals are unavailable. According to the signaling theory, individuals form conditional probabilistic beliefs about given characteristics under information asymmetry, as it is easier to anticipate others' behavior when they are similar to oneself (Akerlof 1970; Spence 1973). In this light, homophily provides baseline expectations of behavior, while longer distance in the social and demographic space implies greater uncertainty, due to the lack of reference frames and social reinforcement.

Importantly, the interpretation of the homophily/distance bias from an informational perspective suggests that the bias could be offset by alternative quality signals, which increase trust in exchange relations (Connelly et al. 2011). User reputation and relational structure moderate the distance bias: the relationship between social distance and trust is conditional on quality, which is related to one's past reputation as reflected by network position and connectivity (Wasko and Faraj 2005).

As exchange relations are dynamic, its underlying social biases evolve with ongoing interactions and experience. Whereas past research suggests that repeated interactions increase trust in economic exchange (Bapna et al. 2017), online transactions are typically swift and one-time (Ba and Pavlou 2002:246). This implies that user experience mainly evolves with renewed platform usage rather than interactions with the same exchange partners, and the direction of bias may depart from the prediction of theories based on repeated offline transactions. The dynamics of rating bias, however, have rarely been examined in the past and remain an important direction to explore for understanding the behavioral trends online.

Investigating the structure and evolution of social biases is particularly important to improving online rating systems, which are feedback mechanisms that guide user choices in the sharing economy as well as other platforms. Under the condition of information asymmetry, it is likely that clear quality signals, such as user reputation in ratings, would be more reliable to generate trust than demographic similarity in a network of strangers (Abrahao et al. 2017). It is, however, critical to identify the sources and distribution of biases, as well as their evolutionary trends among heterogeneous populations. The issue of ratings and trust in the sharing economy is discussed in the following section.

Reputation and Trust in Online Rating Systems of the Sharing Economy

Social exchange is an essential part of the sharing economy, which is facilitated by trust and reputation online. These aspects are reflected by ratings that display the homophily preference as found in offline relationships (Lampe et al. 2007). Users with similar status and characteristics tend to rate each other higher (Anderson et al. 2012) and enter trust relationships (Tang et al. 2012). Despite the robust findings, ratings are influenced by other factors that interact with social distance, which produce a system of bias with complex dynamics that evolves over time.

Whereas homophily is a prevalent tendency, the important issue is what factors counteract the bias in trust formation. Addressing this point helps reduce the behaviors that impair user evaluation. Online interactions differ from offline relationships in which people engage in repeated exchange. This implies that trust is more difficult to form, due to greater risks and uncertainty in arms-length transactions (Ba and Pavlou 2002; Pavlou et al. 2007). Because of the relative anonymity of online connections that lacks face-to-face interactions, user attributes are unclear indicators of quality and trustworthiness. Alternative signals, such as ratings, convey more reliable information on reputation, thus moderating the relationship between social distance and trust. Indeed, a recent study on Airbnb users has found that homophily and trust have a linear correlation for low-reputation users, whereas high-reputation users attract diverse exchange partners regardless of social distance (Abrahao et al. 2017). The findings indicate nonlinear dynamics between social distance and trust, which are moderated by reputation signals.

> *Hypothesis 1: There is a non-linear relationship between social distance and trust, conditional on user reputation from past ratings.*

Rating biases, however, are reinforced in power-dependent exchanges. As ratings reflect socialization online, the party that brings more resources is likely to receive favorable evaluation as a form of reciprocity (Diekmann et al. 2014). According to a study on Couchsurfing, the more resourceful partners (hosts) get higher ratings from guests in an act of status giving (State et al. 2016). This shows the effect of power differentials on evaluation asymmetry. Moreover, the bias from power imbalance may interact with that from social distance if dissimilarity decreases evaluation of the lower-status party. An interaction between power imbalance and social distance hence magnifies rating asymmetry on sharing economy platforms:

> *Hypothesis 2. Power imbalance between exchange partners in the sharing economy has an interaction effect with social distance, as the more powerful party gives lower ratings to partners who are socially distant.*

The structure of rating biases evolves over time, as trust is a dynamic process that is continuously reshaped during ongoing interactions. Three aspects contribute to trust evolution, namely individual characteristics, institution, and process (Zucker 1986). Whereas the first is related to homophily, the second and third depend on institutional structure and individual experience. These aspects play different roles in trust evolution, which arguably increases during repeated exchange (Granovetter 1985; Gulati 1995). The distinctive settings of online platforms, however, suggest a point of departure from the classical association between trust and repeated interactions.

Exchanges online are swift and arms-length, as users revisit platforms without engaging in transactions with the same partners. Whereas users during revisits may have increased trust towards the platform's institutional infrastructure, the generalized trust towards exchange partners does not necessarily increase (Fang et al. 2014; Gefen et al. 2003; Gefen and Pavlou 2012). This means that repeated platform interactions do not translate into more trust towards individuals, especially for users with bad experiences. Whereas lab experiments find that individuals in powerful positions tend to display more power during interactions over time (Cook et al. 1983), increased power use can enlarge rating asymmetry among those in power-dependent relations. This leads to a counterintuitive hypothesis that repeated platform experience does not promote individual trust but increases bias in the long run:

> *Hypothesis 3a: Repeated platform interactions decrease user trust towards exchange partners, especially for those with bad experiences.*

> *Hypothesis 3b: Repeated platform interactions decrease trust for those with more power in exchange relations.*

It is important to note that the evolution of trust online differs from that of reputation signals. While public ratings indicate reputation, they also serve as a means of online reciprocity that compensates for the lack of social reinforcement found offline (Diekmann et al. 2014:68). Exchange partners rarely give negative feedback compared to positive reviews, and repeated platform usage facilitates this socialization process in mutual feedback. Public ratings are inflated as a result, especially when user identities are known to each other (Dellarocas 2003).

The rating inflation suggests that reputation in the long run becomes a less reliable quality signal when many more receive excellent reviews. Reciprocity, however, does not imply generalized trust. Previous studies on sharing economy platforms point out the discrepancy between public and private ratings, as well as reduced inflation when ratings become invisible (Bolton et al. 2013). The evolutionary trend of reputation likely reflects increased reciprocity, which suggests that the baseline of user evaluation shifts over time due to rating inflation in the socialization process.

> *Hypothesis 4: Repeated platform experience inflates public ratings over time.*

Research Design and Analysis

Our project examines the structure and evolution of rating bias in social exchange within the context of the sharing economy. We have acquired a massive Couchsurfing dataset, which includes 1.5 million hospitality interactions since the platform's inception until 2012. Users play the roles of host, surfer, or both, and we have information on their basic demographics such as age, gender, and marital status. A unique feature of the dataset is that it provides ratings in both public and private settings, which differentiate reputation from trust. For a user to establish a tie with others in the network, the service presents them with two mandatory rating tasks that evaluate 1) the strength of friendship and 2) the level of trust. Whereas the friendship scores are publicly visible, the trust scores are confidential. The different ratings of public reputation and private trust present a unique opportunity to examine the structures and coevolution of biases in different domains.

Rating Bias over Social Distance

We first examine the structures of rating biases that vary by social distance among heterogeneous user groups, as well as those who play different roles of hosts and surfers. As hosts have valuable resources on which surfers rely during their stay, the hospitality exchange is a power-dependent relationship in which the hosts have more power.

We start with rating asymmetry among user pairs based on social distance and power-dependent roles. Specifically, we examine the proportions of users who are likely to rate their partners lower (i.e. the proportions are significantly different from 50% as shown by confidence intervals) according to roles, gender and age. Figure 1 reports the proportions of asymmetric ratings in public and private scores, with the first panel from hosts to surfers, the second from women to men, and the third from younger to older (at least 5 years apart in age). The findings show that public ratings display generalized reciprocity among hosts and surfers (Figure 1 first panel), with mutual provision of similar feedback (Lauterbach et al. 2009). The private scores, however, have significant differences, as hosts tend to leave lower scores to surfers. This suggests that the bias from power-dependent roles is likely to reveal when ratings are protected by anonymity, and it is reduced by the expectation of public reciprocity. The second panel reports the rating asymmetry from women to men and shows a gender effect, as women consistently rate men lower in public and private. The third panel shows results from different age groups, with younger users leaving lower friendship scores but higher trust ratings.

The observed patterns show that asymmetric evaluation depends on roles and user features, and it is important to investigate the relationship between bias and social distance in power-dependent exchanges. Using an ecological theory proposed by McPherson (1983), we measure a user pair's difference as the Hamming distance among their demographic attributes, such as age, gender and marital status. Difference in each attribute is measured as 1, which denotes a different gender, marital status, or at least five years apart. The distance metric ranges from 0 to 3, with 0 denoting same attributes for a pair of users, and 3 for the complete opposite.

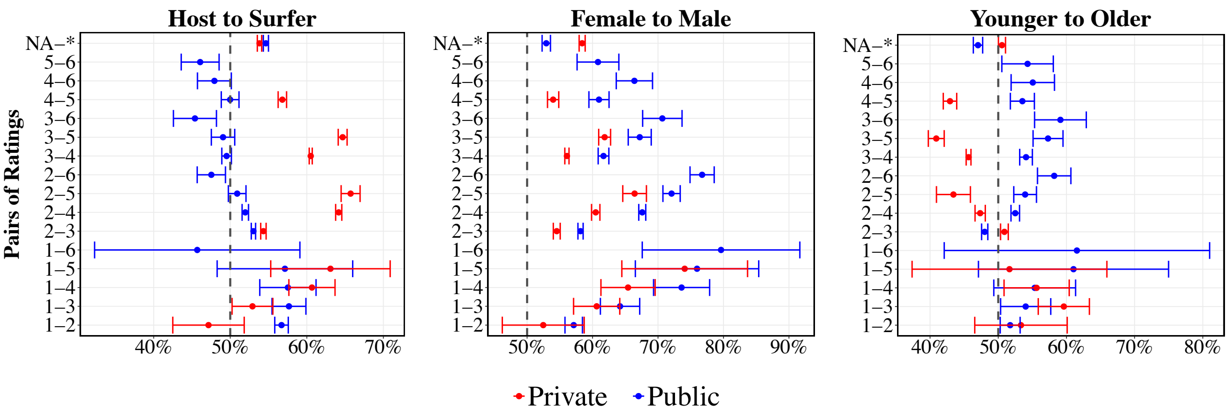

Figure 1. Rating Asymmetry between User Groups

We investigate the impacts of social distance and gender on rating asymmetry between hosts and surfers in Figure 2. We observe that social distance has a nonlinear relationship to rating difference in both public and private domains, whereas the patterns differ for male and female hosts. For male hosts, there are positive differences in public and private scores that first increase and then decrease over social distance, which suggest that male hosts evaluate dissimilar others more positively than those with completely similar characteristics. For female hosts, however, the rating differences over social distance tend towards the negative directions, but the asymmetries are reduced for those with opposite features. The findings imply a nonlinear relationship between social distance and rating bias (Hypothesis 1), which clearly manifests in power-dependent exchanges and differs for men and women. An interaction effect is thus likely to exist between social distance and roles while being moderated by gender (Hypothesis 2).

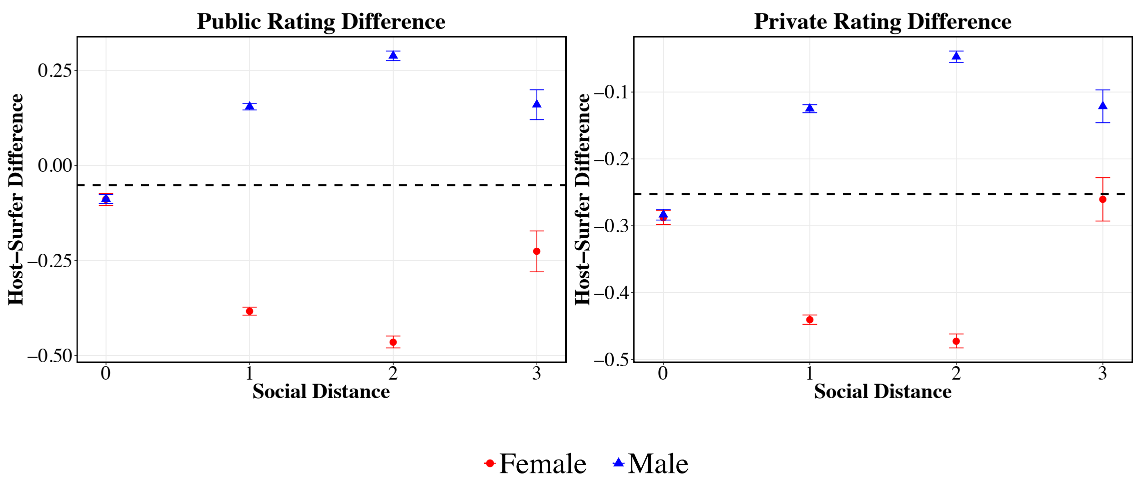

Figure 2. Rating Asymmetry over Social Distance, by Role and Gender

Overall, we observe patterns of homophily and heterophily among Couchsurfing users, and a nonlinear effect of social distance on rating asymmetry. The greatest evaluation bias, however, occurs among those who are somewhat dissimilar. This suggests the targeted population for bias correction in future research design and analysis.

Evolution of Rating Bias

Next, we investigate the coevolution of user reputation and trust over platform experience. Whereas past theories suggest that repeated interactions increase trust, we find that more platform usage inflates reputation and decreases trust, which contrasts with prior predictions but is consistent with Hypotheses 3 and 4.

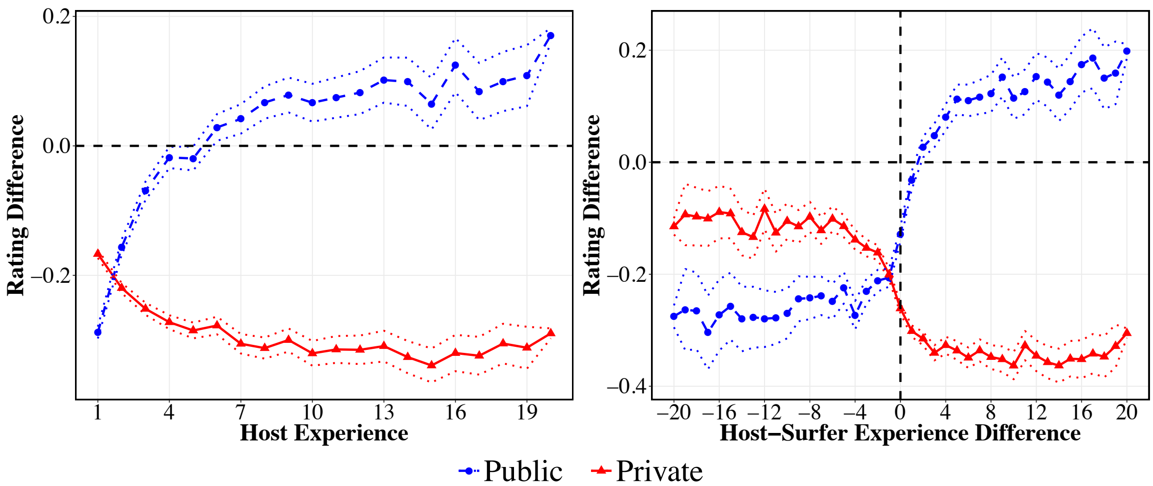

Figure 3. Evolution of Biases in Reputation and Trust over User Experience

Figure 3 left shows the average trends of rating asymmetries between hosts and surfers over host experience in public reputation and private trust. The negative initial differences show that hosts tend to give lower ratings to surfers, which reiterates the finding from Figure 1. As hosts accumulate more experience, however, their public ratings increase and surpass that of surfers. This shows that repeated platform interactions reinforce the norm of reciprocity, leading to reputation inflation (Hypothesis 4). The asymmetry in trust, however, tends towards the opposite direction, as experienced hosts are less likely to trust surfers. This suggests that more platform usage does not increase generalized trust and magnifies the bias in power-dependent exchanges (Hypothesis 3b). A future direction would be exploring trust evolution among users with different experiences, which helps differentiate the impacts of positive and negative priors on future feedback (Hypothesis 3a).

The trends of rating asymmetry, however, also depend on the experience differentials between hosts and surfers. Experienced hosts may accommodate inexperienced surfers (or vice versa) and give different ratings based on their expectations. Figure 3 right examines this issue by plotting the rating difference over the experience gap between hosts and surfers. The findings present an even starker contrast with that on the left: when hosts are less experienced than surfers, they rate surfers as less friendly but trust them more. However, once the hosts become more experienced than the surfers, they give higher public ratings but lower private scores. The discrepancy between the evolution of public and private biases shows the surprising effect of repeated platform experience, which increases reciprocity but reduces trust in the long run.

Methods

We will use multilevel models and machine learning methods to predict rating biases based on the proposed set of features. The dependent variables are dyadic rating asymmetries in reputation and trust between a user pair. The predictive features include user characteristics, experience, and prior reputation. Whereas traditional regression treats units of analysis as independent observations, the multilevel model recognizes the hierarchical interdependencies in data, where individuals are nested within aggregate structures (Snijders and Bosker 1999). Since hospitality interactions on sharing economy platforms constitute an imperfect hierarchy in which surfers are clustered around hosts, the model is appropriate for generating robust inferences. We will further use neural networks to maximize prediction accuracy based on complex feature interactions. Predictive results from neural networks will be compared to traditional machine learning techniques, such as random forest and support vector machine.

Since non-independence between dyads is a major concern in network analysis, we construct a maximally independent edge set as a robustness check. A single host or surfer could generate multiple rating pairs and the scores are potentially correlated, bringing endogeneity to model estimation. Independent sampling in networks is a potential solution; however, it is accomplished through extremely costly procedures by discarding a large number of observations. Since our data are sufficiently large with millions of dyadic interactions, we can afford this robustness check that reduces network endogeneity. Another way to alleviate the endogeneity issue is to use quasi-experiment design, such as matching methods in combination with difference-in-difference model, to generate treatment and control groups with otherwise similar characteristics. Results from the quasi-experiment will be used to for further validation of the analysis.

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